Detection and localization of B-lines in lung ultrasound by weakly-supervised deep learning

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Background, Motivation and Objective

Lung ultrasonography (LUS) is an ultrasound modality that is gaining growing attention from both the clinical and technical community. While most ultrasound applications are impaired by imaging artefacts, it is the artefactual nature of LUS that made it flourish, with (reverberant) B-line patterns associated to many important lung diseases. In this work, we leverage modern deep learning to assist clinicians by automatically detecting and localizing B-lines in real-time from an ultrasound scan. Interestingly, our method only requires image-labels for training and performs simultaneous weakly-supervised co-localization therefrom.

Statement of Contribution/Methods

We acquired freehand ultrasound videos from 10 patients (study number 1089, approved by the ethical committee CEAVNO) with a commercial clinical system, i.e. the Aplio XV (Toshiba, Tokyo, Japan) scanner. The system was used together with an 11L5 linear-array probe, recording a total of 4218 frames across 12 scans. Of these, 7 were used for training, and 5 for testing. Heavy online data augmentation was used to attain high data diversity during training and avoid overfitting. We designed a 12-layer deep convolutional neural network to map input B-mode images to a set of 128 feature maps, which were then spatially averaged to yield 128 features. These features were further processed by a fully-connected network comprising 256 hidden nodes and 2 class outputs to yield B-line detections. We then leverage gradient-weighted class activation mapping to provide an importance-weighted combination of the feature maps for the probability of detection, representing weakly-supervised localization through an aggregation of the spatial activations across all feature maps.

Results/Discussion

Figure 1 shows the result of the proposed method applied to an *in-vivo* freehand sweep. Across all sweeps in the hold-out test set, the method reached a frame-wise detection accuracy of 0.89, accompanied by a sensitivity and specificity of 0.87 and 0.93, respectively. To our knowledge, the proposed method is the first to explore deep learning techniques for B-line detection in LUS. Notably, the method enables detection in real-time, reaching an inference rate of 276 frames/second when exploiting GPU acceleration.

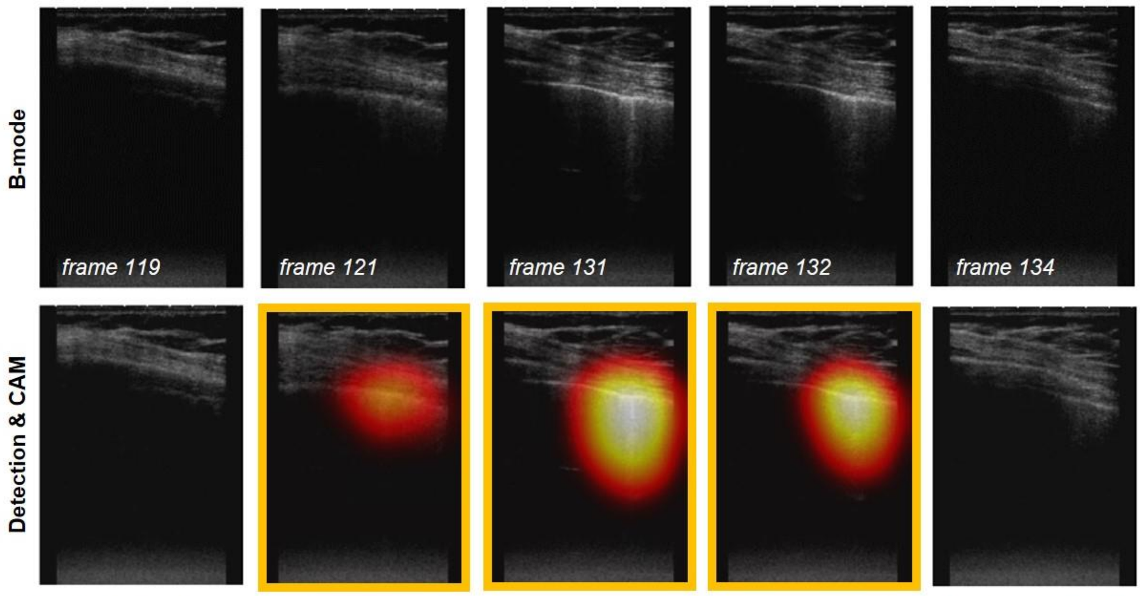

Figure 1. B-mode input data (top) and corresponding class activation maps (CAM) of B-line detection by the deep neural network for an *in-vivo* sweep of a patient from the hold-out test set. Yellow boxes indicate detection.